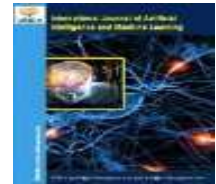


SvedbergOpen
DISSEMINATION OF KNOWLEDGEInternational Journal of Artificial
Intelligence and Machine LearningPublisher's Home Page: <https://www.svedbergopen.com/>

Research Paper

Open Access

High-Capacity Coverless Information Hiding Based On Robust and Deep Learning

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The rapid growth of multimedia communication over public networks has increased the need for secure and reliable information-hiding techniques. Conventional steganography generally embeds secret information by modifying pixels or other carrier components, which can introduce detectable statistical traces and create an attack surface for steganalysis [1]. Coverless Information Hiding (CIH) provides an alternative approach in which the carrier image is not directly modified. Instead, intrinsic image characteristics are extracted and associated with secret information through a mapping mechanism [2–4]. This paper proposes a high-capacity coverless information-hiding framework based on Local Binary Pattern (LBP) hashing, overlapping image blocks, lookup-table mapping, and a Wasserstein Generative Adversarial Network (WGAN). LBP is a computationally efficient texture descriptor originally developed for gray-scale and rotation-invariant texture analysis [5]. WGAN introduces a Wasserstein-distance-based objective intended to improve the stability of adversarial training compared with conventional GAN formulations [6]. The proposed method divides an image into blocks and sub-blocks, extracts LBP-based features, generates 8-bit hash codes, and maps secret information to corresponding image locations. A WGAN-based bidirectional transformation is then employed to generate an independent natural-looking carrier for secure communication. Experimental results reported in the study demonstrate up to **491,520+ bits/image** embedding capacity using a single image. The reported recovery rate is **100%**, with **PSNR = ∞ dB** and **SSIM = 1.000** under the stated experimental conditions. Robustness experiments include JPEG compression, cropping, occlusion, geometric transformations, noise, filtering, and histogram equalization. The proposed framework therefore provides a high-capacity, database-independent approach to coverless information hiding with an emphasis on robustness and reversible secret-data recovery.

Keywords: Coverless Information Hiding, Image Steganography, Robust Hashing, Local Binary Pattern, LBP, WGAN, Deep Learning, Image Mapping, Information Security, High-Capacity Data Hiding.

1. Introduction

The continuous growth of digital communication has resulted in the transmission of a large amount of multimedia information, including images, videos, and text, through public networks. Such multimedia content may contain sensitive information such as personal data, financial information, confidential organizational information, and other private content. Consequently, protecting information during transmission has become an important requirement in modern communication systems [1].

Traditional information-security techniques include cryptography and information-hiding approaches. Cryptography transforms secret information into ciphertext, while steganography attempts to conceal the existence of communication within an apparently innocuous medium [1]. Conventional image steganography generally modifies image pixels or other image components to embed secret information. Such modifications may leave statistical or structural traces that can potentially be detected using steganalysis techniques [1,7].

Coverless Information Hiding does not imply that an image is completely absent from the communication process. Instead, the carrier image can be used without directly modifying its pixels. Image characteristics such as brightness, color, texture, edges, contours, and high-level semantic properties can be used to establish relationships between image content and secret information [3,4]. The fundamental concept of coverless image steganography was introduced to avoid the embedding traces associated with conventional steganography by selecting or mapping naturally occurring image characteristics to secret information [2]. Subsequent research has investigated hashing, feature mapping, image retrieval, and generative approaches for improving the capacity and robustness of CIH systems [3,4].

Existing CIH methods have demonstrated several useful properties, but the research presented in this paper focuses on limitations including dependence on large image databases, communication overhead resulting from multiple images, image-ordering problems, limited robustness against geometric and non-geometric attacks, and the computational complexity of some deep generative models [3,4,8].

Therefore, the central research problem is formulated as follows:

How can a high-capacity, database-independent, and computationally efficient coverless information-hiding framework be designed to provide secure reversible transmission while maintaining robustness against image distortions and network variations?

To address this problem, the proposed framework combines robust LBP-based hashing, overlapping blocks, lookup-table mapping, and WGAN-based image transformation.

2. Related Work

Coverless information hiding has developed through several approaches, including image mapping, feature-based hashing, image synthesis, and generative deep-learning techniques [3,4].

Early coverless approaches selected natural images whose extracted hash sequences corresponded to segments of the secret message, thereby avoiding direct modification of image pixels [2]. Bag-of-Words-based approaches subsequently established relationships between textual information and visual words extracted from images [9]. SIFT- and Bag-of-Features-based methods further investigated robust local features for coverless communication [10]. HOG-based hashing approaches used image-block descriptors to construct hash sequences and demonstrated robustness against several common image-processing operations [11].

Another research direction uses image synthesis. Generative models have been investigated as a means of creating carrier images without directly embedding secret information into an existing cover image [4]. Such approaches can potentially reduce dependence on preconstructed image databases, although generative models introduce additional training and computational requirements. Surveys of CIH research identify **high capacity, high accuracy, robustness, database dependence, and security against steganalysis** as continuing challenges [3,4].

Recent research has also investigated robust hashing and deep-learning-based coverless image steganography. For example, DenseNet-based feature mapping has been proposed to improve robustness against geometric attacks, while other methods have explored DCT/LDA, image retrieval, semantic features, and generative models [8,12,19]. These developments motivate the use of compact local features together with a generative transformation mechanism in the proposed framework.

3. RESEARCH GAP

Based on the literature analysis presented in the research work, several limitations remain in existing Coverless Information Hiding methods.

First, many existing methods depend on large image databases from which suitable carrier images must be selected. This database dependency increases storage and indexing requirements and can increase communication overhead [2–4]. Second, some high-capacity CIH approaches require multiple images to transmit larger secret messages. Third, when multiple images are used, image ordering becomes an important issue because the sender and receiver must maintain consistent image sequences for correct secret reconstruction [3].

Fourth, robustness remains a significant challenge because CIH systems may be affected by image distortions and attacks, including rotation, scaling, translation, noise, filtering, compression, cropping, and other transformations [3,8,12]. Fifth, computational complexity is an important consideration when deep generative models are used. Although WGAN was introduced to improve the stability of GAN training, later research showed that standard WGAN can still encounter convergence and sample-quality issues and proposed gradient-penalty-based improvements [6,13].

Therefore, this research aims to develop a **high-capacity, database-independent, robust, and computationally efficient** coverless information-hiding framework.

4. RESEARCH OBJECTIVES

The proposed research has five major objectives:

1. To develop a high-capacity, secure, and database-independent CIH framework using a single image.
2. To develop robust feature extraction capable of providing transformation-invariant representations.
3. To integrate a Generative Adversarial Network, specifically WGAN, for secure and reversible communication.
4. To achieve reliable secret-data reconstruction under compression, noise, format changes, and other distortions.
5. To improve computational efficiency while maintaining secure communication.

5. Proposed Methodology

The proposed framework consists of five principal stages: **hash-code generation, lookup-table construction, WGAN-based transformation, data embedding, and data retrieval.**

The framework uses Local Binary Pattern features to generate hash codes from image blocks and uses a Wasserstein Generative Adversarial Network to transform the stego representation into an independent carrier image for transmission. LBP is widely used as a computationally simple local texture descriptor and has been demonstrated to provide useful gray-scale and rotation-invariant texture representations [5]. WGAN uses the Wasserstein distance as an alternative training objective for GANs and was proposed to improve training behavior and provide more meaningful learning curves [6].

5.1 Overall Framework

The overall working process can be represented as:

Cover Image → Block Division → LBP Feature Extraction → Hash Generation → Lookup Table → Secret-to-Block Mapping → Stego Representation → WGAN Transformation → Independent Carrier Image → Secure Transmission

At the receiver side:

Independent Carrier Image → WGAN Reverse Mapping → Original Stego Representation → Location-File Decryption → LBP Hash Extraction → ASCII Reconstruction → Original Secret

The complete framework can therefore be divided into two major phases: embedding/transmission at the sender side and retrieval/reconstruction at the receiver side.

During the sender-side process, the cover image is divided into blocks and sub-blocks, and LBP features are extracted to generate hash codes. The secret message is converted into ASCII values and mapped to corresponding image-block locations using the generated hash codes. The resulting representation is subsequently processed through the WGAN to generate an independent carrier image.

At the receiver side, the proposed transformation mechanism is used to recover the corresponding representation. The encrypted location information is then used to identify the required blocks. LBP hashes are recalculated, converted back into ASCII values, and reconstructed to obtain the original secret message.

Important methodological wording: a standard WGAN is a generative adversarial framework; it is not inherently an invertible transformation. Therefore, if your implementation actually performs a learned forward/reverse mapping, the paper should explicitly describe the **specific generator/reconstruction architecture and training objective** that makes this bidirectional recovery possible. WGAN itself should not be cited as proof of invertibility [6,13].

5.2 LBP-Based Hash-Code Generation

Local Binary Pattern is used as the principal feature-extraction mechanism. The original LBP formulation compares neighboring pixels with a central pixel and converts the resulting binary pattern into a local texture code [5].

The image is first divided into blocks of size $L \times L \times L$. Each block is further divided into nine $H \times H \times H$ sub-blocks. LBP features are calculated for each sub-block. Selected features are subsequently represented as an 8-bit binary hash code.

The basic LBP operation is:

$$LBP_{PP,R} = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p \quad LBP_{\{P,R\}} = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p$$

where:

- g_{cg_c} is the center-pixel intensity,
- g_{pg_p} is the intensity of neighboring pixel pp ,
- PP is the number of neighboring pixels,
- RR is the neighborhood radius, and
- $s(x)$ is defined as

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

This formulation follows the standard LBP operator introduced by Ojala et al. [5]. The research implementation subsequently forms an **8-bit representation** for mapping purposes.

6. LOOKUP-TABLE CONSTRUCTION

The lookup table establishes a relationship between hash codes and spatial image locations.

The procedure is:

1. Generate 8-bit hash codes for image sub-blocks.
2. Convert secret characters into ASCII values.
3. Match ASCII values with generated hash codes.
4. Store the corresponding image coordinates.
5. Maintain mapping information in the form:

Hash → Location → Mask Hash → Location → Mask

Hash-based lookup and inverted-index structures are widely used in CIH to efficiently associate image features with secret-message segments [3,4,11].

The lookup table enables efficient identification of the image block associated with each secret character. A location file is subsequently used to preserve the matched block addresses. The presented methodology

also uses masking to prioritize unused blocks and allow repeated characters to be mapped to different blocks.

7. WGAN-BASED SECURE TRANSFORMATION

A Wasserstein Generative Adversarial Network is incorporated into the proposed framework. The original WGAN formulation replaces the conventional GAN discriminator objective with a critic based on the Wasserstein distance and was proposed to improve training stability and reduce problems associated with conventional GAN optimization [6].

A conventional GAN consists of a generator and discriminator. GAN training can suffer from instability and mode-collapse-related problems. WGAN introduced a different optimization formulation intended to provide more stable learning behavior [6]. Subsequent work identified limitations associated with weight clipping and proposed gradient penalty as an alternative [13].

8. INFORMATION-HIDING PROCEDURE

The proposed hiding procedure consists of the following ten sequential steps:

Step 1: Image Preparation

The cover image is resized to fixed dimensions of $M \times N \times 3$ to maintain a consistent input size for subsequent processing.

Step 2: Secret Message Conversion

The secret message is converted into **ASCII values**, where each character is represented by its corresponding numerical ASCII code.

Step 3: Image Partitioning

The resized cover image is divided into smaller **blocks and sub-blocks** to facilitate local feature extraction and secret-data mapping.

Step 4: Hash Generation

Local Binary Pattern (LBP) features are extracted from the image sub-blocks, and corresponding hash values are generated for identifying and representing the blocks [5].

Step 5: Secret-to-Block Mapping

The ASCII values of the secret message are matched with the corresponding LBP-based hash values in the generated lookup table. Each secret character is therefore associated with a suitable image block or sub-block.

Step 6: Location Generation

The **spatial locations** of the matched blocks are recorded. These locations provide the information required to retrieve the corresponding secret characters at the receiver.

Step 7: Masking

A masking mechanism is applied to handle **repeated characters, duplicate mappings, and unused blocks**, thereby maintaining an appropriate block-selection structure.

Step 8: Location Encryption

The generated location information is encrypted using **RSA public-key encryption**. The encrypted location data provides additional security during transmission.

Step 9: WGAN-Based Transformation

The stego representation obtained from the mapping process is passed through the proposed **Wasserstein Generative Adversarial Network (WGAN)-based transformation** to generate an independent image representation.

Step 10: Transmission

The receiver obtains the generated independent image along with the **encrypted location information**. The receiver can subsequently use the corresponding decryption and retrieval procedures to recover the hidden message.

9. INFORMATION RETRIEVAL PROCEDURE

Recovery is performed in two stages.

Stage 1: Stego Representation Recovery

The received independent image is supplied to the trained reconstruction network. The model reconstructs the corresponding stego representation.

Stage 2: Secret Message Reconstruction

The receiver:

1. Decrypts the location file.
2. Identifies target block locations.
3. Calculates LBP hash values.
4. Converts hash values into ASCII values.
5. Reconstructs the original secret character by character.

The use of feature hashes and spatial/index information follows the general retrieval principle used in coverless image steganography [2–4].

10. EXPERIMENTAL SETUP

The proposed framework was implemented using Python/PyTorch on Google Colab. The WGAN model was trained using a generator and critic with the Wasserstein objective and Adam optimization. The experiments considered training for up to 10,000 epochs.

The experimental evaluation focused on hash-code diversity, embedding capacity, WGAN convergence, image quality, recovery accuracy, and robustness against different image attacks.

The evaluated attacks included JPEG compression, cropping, occlusion, rotation, scaling, translation, shearing, perspective transformation, Gaussian noise, salt-and-pepper noise, speckle noise, filtering, and histogram equalization. Such attack categories are relevant to CIH evaluation because prior research has specifically examined robustness under compression, noise, scaling, rotation, filtering, and related image-processing operations [3,8,11,12].

10.1 Experimental Parameters

Table 1: Experimental Parameters for input dataset

Parameter	Experimental Setting
Programming Environment	Python
Deep Learning Framework	PyTorch
Platform	Google Colab
Deep Learning Model	WGAN
Network Components	Generator + Critic
Optimizer	Adam
Maximum Training Epochs	10,000
Hashing Technique	LBP [5]
Hash Code	8-bit
Image Size	512 × 512
Block Size	9 × 9
Sub-block Size	3 × 3
Block Overlap	2/3
Main Evaluation	Capacity, PSNR, SSIM, Recovery
Compression Test	JPEG
Other Tests	Geometric and non-geometric attacks

10.2 WGAN Training Chart

The reported WGAN loss decreases progressively from **9.845 at 1,000 epochs to 0.012 at 10,000 epochs**. This represents the training trend reported in the experimental results.

Table 2: WGAN Training Loss

Epoch	Wasserstein Loss
1,000	9.845
2,000	8.214
3,000	6.756
4,000	5.123
5,000	3.674
6,000	2.041
7,000	0.842
8,000	0.214
9,000	0.058
10,000	0.012

These numerical values should be described as **experimentally observed values from the proposed implementation**, rather than as values established by the WGAN literature.

10.3 Experimental Observation

The experimental results show a continuous decrease in the reported WGAN loss as the number of training epochs increases. The loss decreases from 9.845 to 0.012, indicating the convergence trend observed for the proposed model.

The research presentation associates this trend with stable training, smooth convergence, improved image generation, and reduced mode-collapse behavior. However, the claim of reduced mode collapse should ideally be supported by an explicit experimental measure or qualitative/generated-image analysis rather than inferred from loss alone. The original WGAN paper discusses improved training behavior and meaningful learning curves [6].

For the overall evaluation, the proposed framework reports:

- 491,520+ bits/image capacity
- 100% recovery
- PSNR = ∞ dB
- SSIM = 1.000

under the stated experimental conditions.

11. Results And Discussion

11.1 Hash-Code Diversity

Each sub-block generates an 8-bit hash code, theoretically providing up to:

$$2^8 = 256^2 = 256$$

possible binary values.

The overlapping-block strategy is reported to increase feature diversity and reduce repetition. For the evaluated images **Lenna**, **Baboon**, **Cameraman**, **Tulips**, **Deer**, and **Peppers**, the overlapping-block experiments report 256 distinct values for the average-based, median-based, and hash-based approaches. The use of local texture information for compact binary representation is consistent with the fundamental LBP concept [5].

11.2 Effect of Block Size

The experiments evaluate block sizes from $9 \times 9 \times 9$ to $24 \times 24 \times 24$.

The reported results indicate that smaller blocks capture finer texture information and generally produce greater hash diversity. The $9 \times 9 \times 9$ to $15 \times 15 \times 15$ configurations frequently reach the maximum reported value of 256 distinct hash codes, while larger blocks show a gradual reduction.

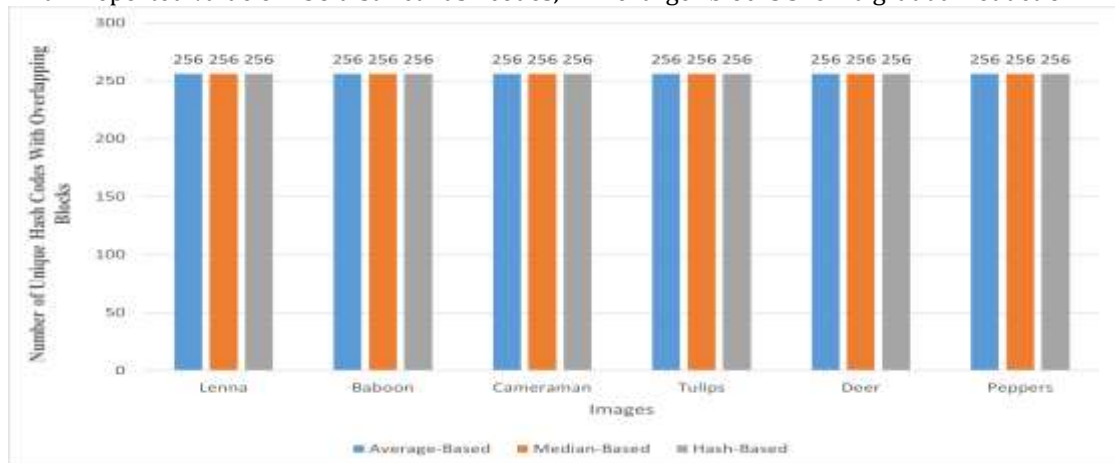


Fig. 1: Number of Unique Hash Codes with Overlapping Blocks

11.3 Embedding Capacity

The proposed method uses an 8-bit hash representation for each sub-block. Consequently, the total capacity depends on the number of available sub-blocks and the mapping strategy.

The experiment uses:

- Image size: 512×512
- Block size: 9×9
- Sub-block size: 3×3
- Overlap: 2/3 of block width

The reported capacity with overlapping blocks is:

$$491,520+ \text{bits/image}$$

The presentation reports that increasing overlap increases the number of usable sub-blocks and therefore increases the embedding capacity.

Table 3: Capacity Comparison

Method	Reported Capacity
Zheng et al.	18 bits/image
Faster-RCNN	20–25 bits/image
MSIM	36 bits/image
Zou et al.	80 bits/image
Abdulsattar	6,272 bits/image
Proposed Method	491,520+ bits/image

The individual comparison values should be cited to the **original papers**, not to a general CIH survey. The literature confirms that capacity is a major limitation in conventional hash-based CIH approaches [3,4]. For

example, existing approaches based on image hashes can have capacity constrained by hash length and the diversity of available image representations [3].

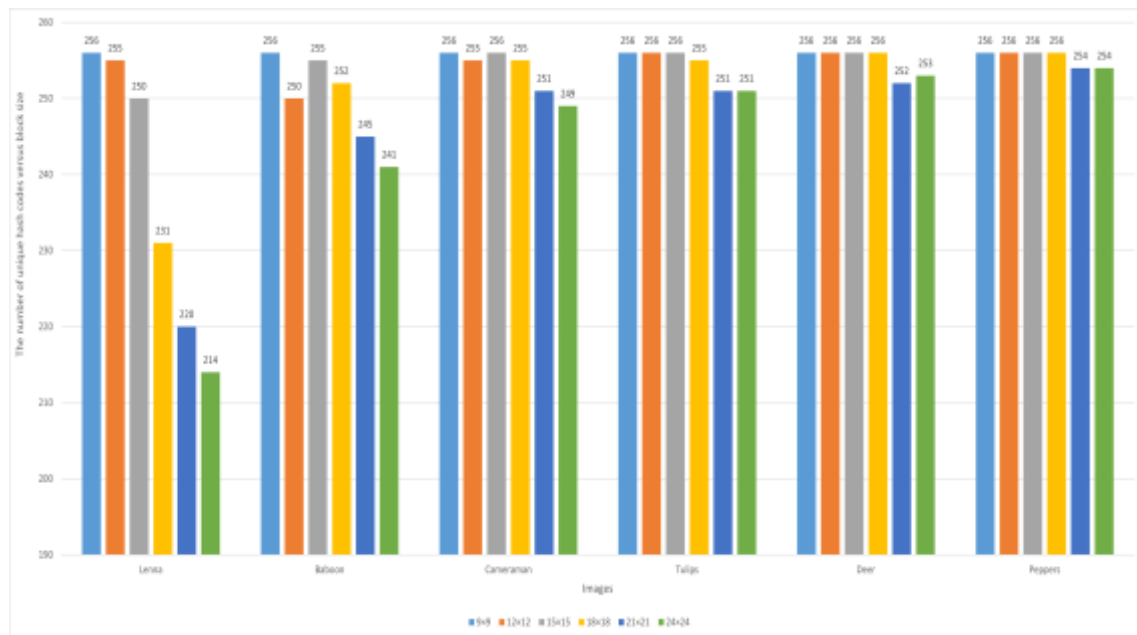


Fig. 2: Number of Unique Hash Codes Verses Block Size

12. WGAN TRAINING PERFORMANCE

The reported Wasserstein loss decreases as training progresses:

Table 4: Wasserstein loss decreases as training progresses

Epoch	Wasserstein Loss
1,000	9.845
2,000	8.214
3,000	6.756
4,000	5.123
5,000	3.674
6,000	2.041
7,000	0.842
8,000	0.214
9,000	0.058
10,000	0.012

The proposed study interprets this trend as evidence of progressively improving training behavior. WGAN was specifically introduced to improve GAN optimization behavior and provide more informative learning curves [6]. However, loss values should be interpreted together with generated-image quality and reconstruction measurements rather than being treated as a standalone proof of image realism or absence of mode collapse.

13. IMAGE QUALITY ASSESSMENT

Two important image-quality measures are considered.

Peak Signal-to-Noise Ratio

PSNR evaluates the distortion between two images.

Structural Similarity Index

SSIM evaluates structural similarity between images.

The reported proposed results are:

PSNR= ∞ \boxed{PSNR= ∞ } SSIM=1.000 \boxed{SSIM=1.000}

with a reported recovery rate of:

100% \boxed{100\%}

The comparison presented in the research material reports PSNR values from approximately

34.76 dB to 52.024 dB for the listed existing methods, while the proposed method reports infinite PSNR and SSIM of 1.000.

Important: PSNR = ∞ and SSIM = 1 generally indicate identical images under the corresponding calculation. Therefore, the paper should clearly specify **which two images are being compared**—for

example, original stego representation versus reconstructed stego representation. If the comparison is between an image and itself, these values do not demonstrate imperceptibility of a transformation.

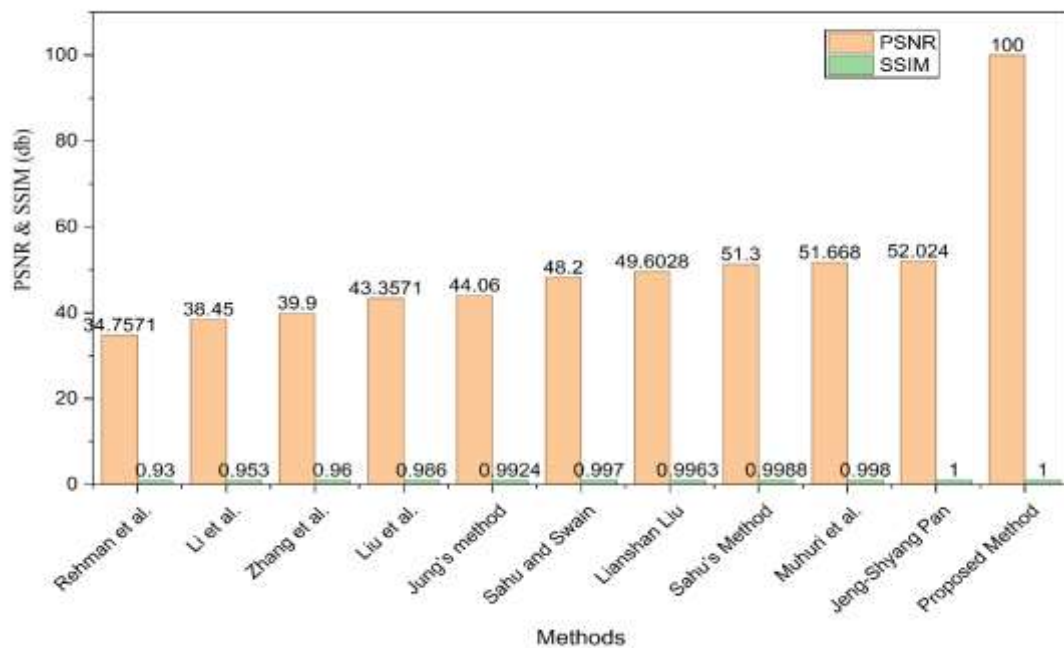


Fig. 3: PSNR & SSIM comparison with respect to methods

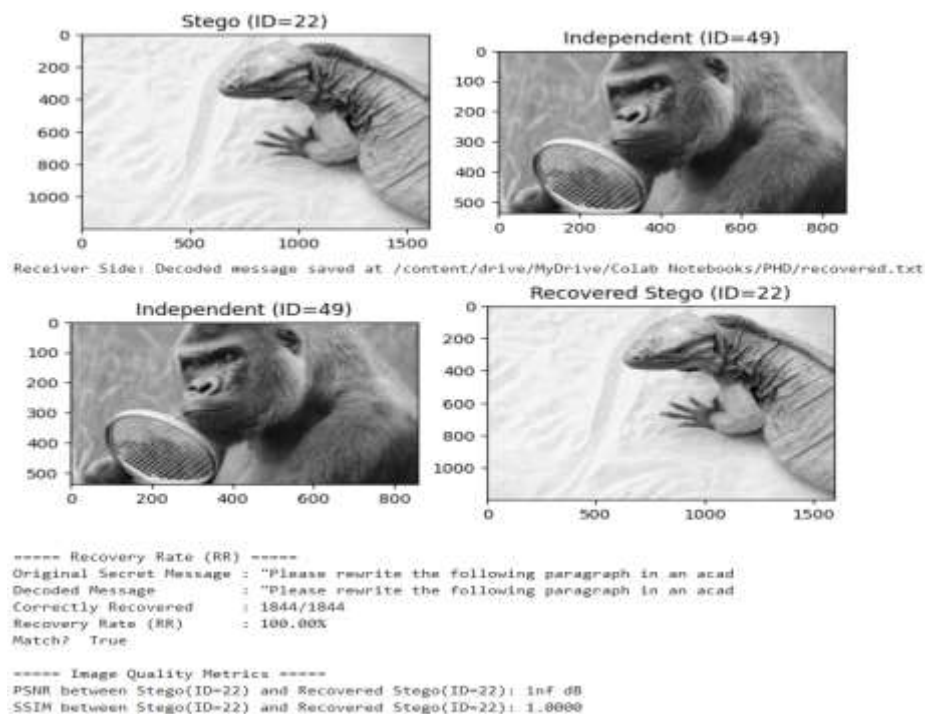


Fig. 4: PSNR & SSIM comparison for image quality

14. NUMBER OF IMAGES REQUIRED

A major objective is to reduce the number of carrier images required for transmitting large secret messages. The presentation reports that some existing methods may require up to **1,024 images for a 1 KB secret message**, whereas the proposed approach reports **one image** for the listed message sizes of 1 byte, 10 bytes, 100 bytes, and 1 KB.

The reduction of image/database dependence is consistent with a recognized research challenge in coverless steganography. Early CIH methods commonly relied on image databases and image retrieval to match secret-message segments with natural images [2–4]. Therefore, the proposed single-image design directly addresses an established limitation.

15. RECOVERY ACCURACY

The proposed mechanism is reported to reconstruct the original stego representation even when the transmitted image is manipulated.

The reported performance is:

Recovery Rate=100%\boxed{Recovery\ Rate=100\%}

and:

BER=0\boxed{BER=0}

for the stated experimental conditions.

These values should be explicitly identified as **experimental results of the proposed implementation**.

16. ROBUSTNESS AGAINST GEOMETRIC ATTACKS

The experiments consider:

- Rotation
- Scaling
- Translation
- Shearing
- Perspective transformation

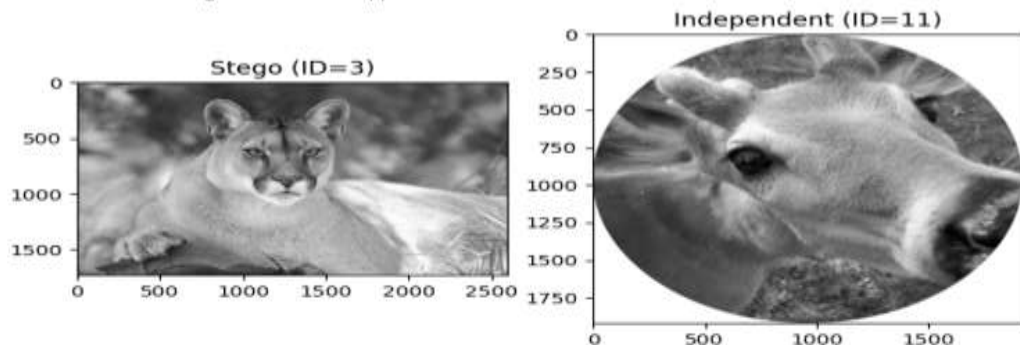
The proposed approach reports **100% recovery** across the listed test conditions.

For example:

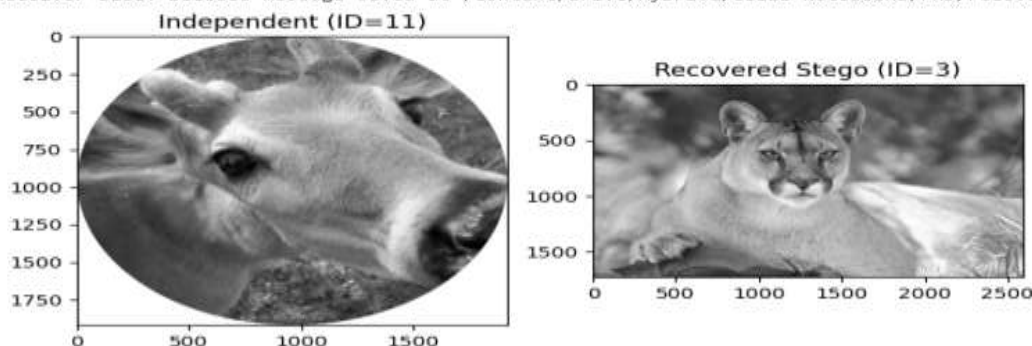
- Rotation: 5°, 10°, and 15°
- Scaling: 0.5×, 0.75×, and 1.5×
- Translation: 25 and 50 pixels
- Shearing: 0.05 and 0.1
- Perspective transformation: 5%

Geometric robustness is an important issue in CIH research because several existing feature-mapping methods exhibit reduced performance under geometric transformations [8,12].

Sender Side: Message hidden & mapped.



Receiver Side: Decoded message saved at /content/drive/MyDrive/Colab Notebooks/PHD/recovered.txt



```

===== Recovery Rate (RR) =====
Original Secret Message : The internet is a crucial medium for transporting
Decoded Message        : The internet is a crucial medium for transporting
Correctly Recovered    : 171/171
Recovery Rate (RR)     : 100.00%
Match? True
/usr/local/lib/python3.12/dist-packages/skimage/metrics/simple_metrics.py:168: RuntimeWarning: di
  return 10 * np.log10((data_range**2) / err)

===== Image Quality Metrics =====
PSNR between Stego(ID=3) and Recovered Stego(ID=3): inf dB
SSIM between Stego(ID=3) and Recovered Stego(ID=3): 1.0000
    
```

Fig. 5: PSNR & SSIM comparison for robustness

17. ROBUSTNESS AGAINST NON-GEOMETRIC ATTACKS

The evaluated non-geometric attacks include:

- Gaussian noise
- Salt-and-pepper noise
- Speckle noise
- Median filtering
- Mean filtering
- Gaussian filtering
- Histogram equalization

The proposed column reports **100% recovery** for all listed conditions.

Previous CIH studies have similarly evaluated noise, filtering, brightness/contrast changes, and other image-processing operations as part of robustness analysis [3,11,12].

18. ROBUSTNESS AGAINST COMPRESSION

JPEG compression is evaluated using quality factors ranging from 10 to 90.

The reported proposed-method result is:

Recovery=100%\boxed{Recovery=100\%} BER=0\boxed{BER=0}

under the stated experimental conditions.

JPEG compression is a standard robustness test in image-hiding and coverless-steganography research [3,8,12].

19. CROPPING AND OCCLUSION

Cropping and occlusion remove portions of image content and can therefore affect conventional image-based retrieval and hashing methods.

The proposed approach is reported to maintain **100% payload recovery** when the transmitted image is cropped or partially occluded. The presentation specifically reports recovery when more than 50% of the image is missing under the stated experimental setup.

Because this is an unusually strong robustness claim, the final paper should include the **exact crop/occlusion ratios, test images, number of trials, and recovery table** so that the result can be independently reproduced.

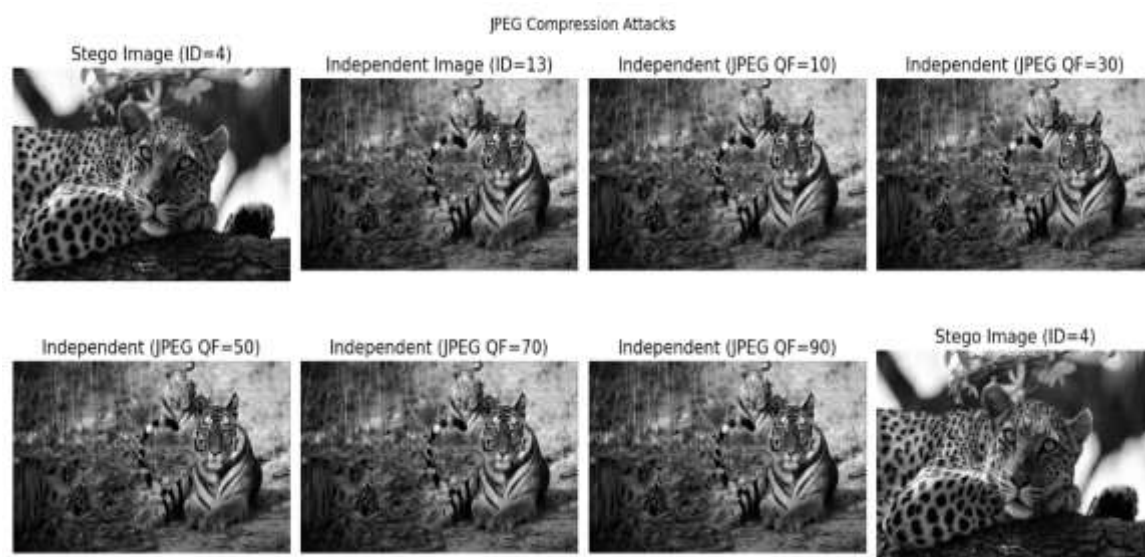


Fig. 6: JPEG Compression Attacks

20. OVERALL COMPARISON

Table 5: Overall Comparison

Evaluation Parameter	Proposed Framework
Database dependency	No large database required
Main feature	LBP-based hashing
Hash size	8 bits
Block strategy	Overlapping
Reported capacity	491,520+ bits/image
WGAN	Yes

Recovery rate	100%
BER	0 under reported tests
PSNR	∞ dB
SSIM	1.000
JPEG robustness	100% reported recovery
Geometric robustness	100% reported recovery
Non-geometric robustness	100% reported recovery
Cropping/occlusion	100% reported recovery

The database-independent direction is consistent with recent CIH research that has attempted to reduce dependence on large collections of natural images [3,4,14].

21. CONTRIBUTIONS

The major contributions of the proposed research are:

1. A high-capacity CIH framework based on LBP hashing and overlapping blocks.
2. A mapping mechanism that associates secret information with image-block locations.
3. A WGAN-based transformation for generating an independent carrier image.
4. A single-image high-capacity hiding mechanism.
5. Evaluation under geometric and non-geometric attacks.
6. Evaluation of compression, cropping, and occlusion robustness.
7. Reported recovery accuracy of 100% under the tested conditions.
8. A database-independent communication framework.

The combination of feature hashing and generative transformation extends the established CIH paradigm from image selection/mapping toward learned carrier generation [3,4].

22. LIMITATIONS

The current research also identifies several limitations.

First, the implementation has primarily been evaluated on grayscale image datasets. Second, overlapping block extraction increases computational complexity compared with non-overlapping approaches. Third, the framework depends on maintaining a secure lookup table and location-information file. Fourth, the experimental evaluation uses benchmark datasets and therefore requires additional validation on larger real-world image collections. Finally, WGAN training requires substantial computational resources and training time.

These limitations are important because CIH research continues to face trade-offs among capacity, robustness, database dependence, computational complexity, and security [3,4].

23. Conclusion

This paper presented a high-capacity coverless information-hiding framework based on robust LBP hashing, overlapping image blocks, lookup-table mapping, and WGAN-based image transformation. Unlike conventional pixel-level steganography, the proposed approach does not rely on direct modification of the carrier image. Instead, secret information is represented through relationships between image features and spatial locations, following the general principle of coverless information hiding [2–4].

The reported experiments demonstrate a capacity of up to **491,520+ bits per image**, enabling high-capacity communication using a single image. The framework also reports **100% recovery, PSNR = ∞ dB, and SSIM = 1.000** under the specified experimental conditions. Robustness experiments cover compression, cropping, occlusion, geometric transformations, noise, filtering, and histogram equalization. The results indicate that the combination of robust hashing and deep generative transformation provides a promising research direction for high-capacity coverless information hiding. At the same time, the identified limitations—including grayscale evaluation, computational cost of overlapping blocks, lookup-table security requirements, benchmark-dataset dependence, and WGAN training cost—provide important directions for further research. WGAN-based generation should also be distinguished from genuinely invertible generative architectures when describing the recovery mechanism [6,13].

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